Exploration of the Usage of Color Terms by Color-blind Participants in Online Discussion Platforms

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Abstract

Prominent questions about the role of sensory vs. linguistic input in the way we acquire and use language have been extensively studied in the psycholinguistic literature. However, the relative effect of various factors in a person's overall experience on their linguistic system remains unclear. We study this question by making a step forward towards a better understanding of the conceptual perception of colors by color-blind individuals, as reflected in their spontaneous linguistic productions. Using a novel and carefully curated dataset, we show that red-green color-blind speakers use the "red" and "green" color terms in less predictable contexts, and in linguistic environments evoking mental image to a lower extent, when compared to their normal-sighted counterparts. These findings shed some new and interesting light on the role of sensory experience on our linguistic system.

1 Introduction

Colors play an exceptionally prominent role in our lives. Simple and vivid, and yet so difficult to describe or reduce to linguistic terms, our experience of color has long raised intriguing questions concerning grounded color semantics – quantifying the associations between words and perceptual representations – to philosophers, scientists, and psycholinguists (Chuang et al., 2008; Heer and Stone, 2012). McMahan and Stone (2015) have shown that the subjective quality of color experience varies between individuals. A body of work in color semantics have indicated that color lexicalization and usage patterns can be significantly affected by extra-linguistic factors, such as culture, physical environment (Athanasopoulos, 2011; Josserand et al., 2021), and the native language of a speaker (Sarantakis, 2014; Matusevych et al., 2018).

How do colors appear to color-blind individuals? Does the imperfect perceptual experience of red and green in people with red-green visual deficiency (*deuteranopia*) shape their color-related linguistic production? Embodied cognition theory poses that the entirety of our sensory experience – activities that help us develop a better understanding of word semantics by using our five senses – shapes our conceptual knowledge (Barsalou et al., 2008; Foglia and Wilson, 2013). As an example, reading the word "cat" is likely to elicit sensory experiences we have with cats, such as their sound and how they look. Embodied cognition theory thus assumes that all our sensory experiences contribute to our conceptual knowledge and processing, which, in turn, is reflected in our language.

Related Work Prior work on the effect of color-blindness on language production is relatively sparse. Landau and Gleitman (2009) studied the language of *blind* children, focusing (among others) on the achievements of three blind children's in the area of syntax and word learning. The authors found general development patterns similar to those by their sighted agemates. Representation of colors in blind and color-blind individuals was studied in a controlled color-similarity experiment with 37 participants – 15 red-green color-blind, among others (Shepard and Cooper, 1992). The participants were asked to rank the degree of similarity between colors, when presented with names-only, visual colors only, and names+color stimuli. While significant differences in the similarity judgments were found for the color-only setting, when color-deficient participants were presented with names along with the colors, their rankings became closer to those by normal-sighted people. This suggests that linguistic exposure plays a considerable role in shaping our perception of color representation. Multiple works have studied the language of visually impaired and blind children at various stages of language development, suggesting evidence for difficulties in just those areas of language acquisition

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where visual information can provide input about the world, stimulating hypotheses about pertinent aspects of the linguistic system (Andersen et al., 1984; Pérez-Pereira and Conti-Ramsden, 2013).

The puzzling question on the role of sensory vs. linguistics input in shaping our color perception remains therefore sound. In this work, we make a step forward towards better understanding of the conceptual perception of the red and green colors in red-green color-blind individuals, as mirrored in their spontaneous linguistic production.

We perform a first (to the best of our knowledge) large-scale computational study on the usage of the "red" and "green" color terms in (self-reported) population with *deutan* and *protan* visual impairment. Using a novel dataset of linguistic productions by color-blind (CB) individuals, we show that they use the "red" and "green" color terms in less predictable contexts, and in linguistic environments evoking mental image to a lower extent, when compared to normal-sighted (NS) authors.

The contribution of this study is, therefore, twofold: First, we release a large, diverse, and carefully curated dataset of linguistic productions by red-green CB authors, accompanied by a corpus of utterances by NS individuals, aligned on various linguistic properties. Second, we show preliminary evidence for subtle, yet reliably detected, divergences in the usage of "red" and "green" by CB speakers, compared to their NS counterparts. We make the dataset and our code available for facilitating future research in this field.[1]

2 Datasets

We collected datasets used in this work from Reddit – an online community-driven platform consisting of numerous forums for news aggregation, content rating, and discussions. As of 2021, it had over 430 million monthly active users, positioning it as the sixth most popular social site in the US. Content entries are organized by areas of interest called subreddits, ranging from main forums that receive extensive attention to smaller ones that foster discussion on niche areas.

2.1 Collection of Posts by CB Users

Multiple subreddits allow their contributors to specify a *flair* – a metadata attribute adding context to the specific subreddit, such as country of origin, political association, occupation, age, etc. We collected the set of color-blind Reddit authors from `r/colorblind`, considering only those self-reported as having one of the red-green color blindness types we study in this work: *deuteranopia*, *deuteranomaly*, *protanopia*, and *protanomaly*. This procedure resulted in $2,523$ authors in total. Using the collected list of user IDs, we were further able to retrieve their entire digital footprint from Reddit, spanning years 2005 through 2021.

Manual inspection of utterances produced by the color-blind Reddit users reveals that CB authors occasionally discuss various aspects related to the impairment, as in *"this game's color-scheme is not a good fit for colorblind, I cannot tell red from green"*. Aiming at the analysis of deficiency-agnostic linguistic productions, we apply strict filters on user utterances, by excluding (1) sentences originating from a manually collected list of subreddits potentially related to the color blindness phenomenon, and (2) sentences containing words possibly indicative of the CB impairment, such as "color", "colorblind", "vision", their inflections and spelling alternatives (e.g., "colour"), to prevent potential biases stemming from deficiency-related discussions. The full list of excluded subreddits can be found in Appendix A.1.

2.2 Collection of Posts by NS Users

The comparative nature of our analysis requires a collection of utterances produced by normal-sighted Reddit authors. Assuming the relatively low ratio of $\sim 8\%$ of people with the CB deficiency in the population (Wong, 2011), we sampled a large set of posts and comments from the general population of Reddit authors, excluding the (self-reported) set of CB users. We believe that this approach largely targets the language of NS authors due to their large numbers and extensive diversity.

Usage patterns of color terms in linguistic productions can be affected by several dimensions: demographic factors (gender, age), language modality (spoken vs. written), linguistic register (formal vs. informal), topical preferences, etc. Multiple works have shown that there exist detectable differences in the language of male and female speakers, and that topical tendencies shape both the frequency and contextual environment of word usage. Therefore, we strived to create a control set of NS productions that would be aligned with CB language

[1] Code is available at `https://github.com/IBM/colorblind-language`; complying with Reddit's terms of use, we provide a full pipeline for re-producing the dataset (extraction and filtering), rather than the data itself.

across these dimensions. While achieving a perfect alignment is impractical, we controlled for two major dimensions – gender and topic – while sampling linguistic productions by NS authors.

Balancing Posts by Author Gender Color blindness affects approximately 1 in 12 men (8%) and 1 in 200 women (0.5%) in the world (Wong, 2011). Because most commons roots of color blindness are genetic, passed along the X-chromosome, people with XY chromosomes (most men) only need one defective chromosome (X) to have the deficiency (Wong, 2011). Roughly speaking, the phenomenon is 16 times more frequent in men than in women. The imbalanced 2:1 ratio of male (M) to female (F) Reddit authors[2] imposes an additional prior distribution to the ratio of men vs. women in the color-blind population of Reddit, increasing the estimated frequency of color-blind male authors to be 32 times higher than that of female in our data.[3]

A large body of research has shown that the language of female authors differs from that of their male counterparts, exhibiting both topical and stylistic divergences (Lakoff, 1973; Holmes, 1984; Labov, 1990), to the extent that texts written by the two genders are separable automatically (Koppel et al., 2002; Argamon et al., 2003; Rabinovich et al., 2017). Gender-linked differences in human color lexicon, preferences, and perception have been reported in the literature (Arthur et al., 2007; Eckert and McConnell-Ginet, 2013), suggestive of their effect on both the frequency and contextual linguistic environments of color terms. A valid control set of authors should, therefore, maintain the same M:F author ratio as in the CB set, i.e., 32:1.

Recently, Rabinovich et al. (2020) released a large dataset of posts and comments collected from the Reddit discussion platform, where each sentence is annotated by the (self-reported) binary author gender. We exploit this dataset by making use of utterances by $13,630$ male users, and by (randomly downsampled) 425 female users, preserving the 32:1 M:F author ratio and resulting in the total of $14,055$ authors[4] and over 45M posts.

Balancing Posts by Topical Threads Usage patterns of words, and in particular, color terms, are likely to be affected by their contextual environment. As an example, using color terms in a topical thread (subreddit) related to interior design will differ from that of gaming, health, or world news.

Aiming at similar topical distribution in both CB and NS sets, we balance the distribution of sentences in various subreddits across the two populations, by (1) splitting the data at the sentence-level, (2) using the CB subreddit distribution as the anchor, and (3) performing *stratified sampling* of NS data to maintain the same relative topical ratios. Specifically, let $\mathcal{R}$=$(r_1, r_2, r_3, ..., r_n)$ be the relative ratios of the amount of sentences spanning n subreddits in the CB dataset, where $\sum r_i$=1; the set of NS sentences is then randomly downsampled in a manner preserving the topical distribution $\mathcal{R}$. Although the absolute number of sentences differs significantly in the two datasets, the relative ratio of each topical thread is roughly preserved.

2.3 Color Terms used in this Study

We address our research questions by performing contrastive analysis of the usage patterns of "red" and "green", as well as additional eight color terms exceeding the total count of 1000 in our CB dataset: "black", "white", "blue", "brown", "gr[ae]y", "yellow", "pink" and "purple".[5] This resulted in the total number of over 80K and 380K sentences, each including at least one of the ten color terms, for the CB and NS populations, respectively. Differences (if they exist) are anticipated to be linked to the CB-deficiency, therefore evident in the usage of "red" and "green" terms, but not the others.

2.4 Fixed Expressions and Named Entities

Color terms are often used in fixed linguistic expressions – groups of words used together to express a particular idea or concept that is more specific than the literal combination of individual words. Among such expressions are "black music", "red army", "green energy", etc. Both the production and comprehension of such expressions is unlikely to evoke a visual image of color in one's mind, hence processing of these terms does not rely on the ability to visually distinguish between colors. Therefore, we excluded expressions with salient non-compositional nature from this work.

A subset of expressions exceeding the 0.5% relative frequency among the full set of <color-term NOUN> adjective phrases considered in this work

[2] According to statistics in shorturl.at/doH02.

[3] The collection of color-blind authors does not contain gender markers; therefore, applying the general Reddit prior to our set of CB authors is a plausible choice.

[4] Authors with self-reported gender that also indicated their color blindness defect, were excluded from this set.

[5] With an exception of "purple" that has 943 occurrences.

was examined by a native English speaker. Out of 220 unique expressions, 140 were marked as having a common fixed reading, or referring to named entities, such as sport teams ("Green Bay", "Blue Jays"), bands ("Green Day"), or video games ("Red Redemption"). This procedure resulted in excluding about 25% of sentences; the complete list of excluded expressions can be found in Appendix A.2. Table 1 presents the statistics of our final dataset, spanning over 30K subreddits. We also report the statistics of two complementary CB datasets released with this work: the collection of posts by authors with blue-yellow color blindness (*tritanopia*) and monochrome vision (*achromatopsia*), to facilitate further research in this field.

dataset	users	# sent (# with a color term)
protan (CB)	1,067	4.1M (24K)
deutan (CB)	1,456	6.0M (36K)
total red-green CB	2,523	10.1M (60K)
normal-sighted (NS)	14,055	45.7M (280K)
tritan (CB)	236	386K (3.8K)
monochrome (CB)	47	100K (589)

Table 1: Details of the datasets. # of sentences including one of the color terms is in parentheses. Red-green CB and NS are used in this work; the additional tritan and monochrome datasets are released as well.

3 Research Questions

The two sub-corpora represent a suitable testbed for investigating questions about the unique linguistic phenomena characteristic of red-green CB authors, compared to the NS population of Reddit users. Here, we elaborate on the research questions addressed in this study.

RQ1 How does the frequency of color terms in linguistic productions of CB users compare to that of NS speakers? We refer to (1) the frequency of color terms in the language, and (2) the relative frequency ratio of individual color terms – in particular, "red" and "green" – within the entire set of the ten color terms considered in this work.

RQ2 Red-green color blindness affects the ability to generate a clear (and distinguishable) mental image of these two colors in the mind of a speaker, giving rise to the hypothesis that CB authors would be more hesitant when using these two color terms in linguistic environments evoking a visual image in one's mind. Such linguistic environments can be commonly found in topical threads involving visual experience, such as `r/gaming`, `r/nature` or `r/fashion`. Focusing on *adjective phrases* with color-terms – *attributive* (e.g., "red/ADJ shirt/NOUN") or *predicative* (e.g., "this shirt/NOUN is red/ADJ") – we test this hypothesis by searching for detectable differences in the psycholinguistic property of the modified nouns' *imageability* – a measure of how easily a physical object, word, or environment evokes a clear mental image in the mind of a person observing it (Cortese and Fugett, 2004; Scott et al., 2019).

A common way to study perceptual aspects related to language in psycholinguistic literature distinguishes between nine major psycholinguistic dimensions, including imageability. Scott et al. (2019) released a set of $5,500$ English words manually ranked along the nine dimensions on the 1-7 scale, facilitating much research in psycholinguistics and related fields (Lewis and Lupyan, 2020; Lynott et al., 2020; Rabinovich et al., 2020). As a concrete example, the word "piano" has a ranking of 6.88 in the imageability dimension, while "request" was only assigned the score of 2.50.

We use the rankings by Scott et al. (2019) to investigate if detectable differences can be found in the imageability properties of nouns modified by the "red" and "green" color terms, as employed by red-green CB vs. NS authors.

RQ3 Multiple factors influence our lexical choices. Linguistic evidence, extra-linguistic experience, and psychological factors affect the way we employ various linguistic devices in a context. Permanent lack of or deficiency in a sensory input may influence our word usage (Andersen et al., 1984; Pérez-Pereira and Conti-Ramsden, 2013). One such effect can potentially be manifested by more *conservative* or, on the contrary, more *atypical* usages of a linguistic device. Considering the impaired visual experience in CB users, here we ask if the contextual usage of the "red" and "green" color terms differs between the two populations.

We investigate this question by quantifying the *contextual predictability* of various color terms in the two populations. Contextual predictability of a linguistic unit defines how probable it is in some local environment, thereby providing a way to estimate the differences in the likelihood of color terms in that given context. Higher predictability would be indicative of more common usage patterns; lower predictability – of less typical choices.

4 Experiments

4.1 Experimental Setup

We test the suggested research questions on the usage of the "red" and "green" color terms, and compare the findings to usage patterns of the additional eight color terms, as listed in Section 2. We strengthen these findings by performing similar comparative tests on two control sets, where we do not anticipate differences between CB and NS. All differences were tested for significance, where Bonferroni correction was applied with m=20.

Control Set #1: Matched Adjectives Focusing on the most common syntactic role of color terms in the English language (almost 80% of all color terms are tagged as ADJ in the POS-tagged Wikipedia dump), we apply the same set of experiments on ten adjectives matched on frequency and length (±1 character) with the ten color terms. The adjectives include "hot", "flat", "social", "clear", "tiny", "loose", "lame", "petty", "clever", "royal". Differences detectable in "red" and "green", but not in this control set, would be indicative of phenomena unique to "red" and "green" in CB vs. NS authors.

Control Set #2: NS Authors Random Split As an additional control set, we perform a random split of all normal-sighted users preserving the CB:NS user ratio similar to that in the main corpora, as well as gender and stratified topical balance (see Section 2.2 for details). Differences evident in the "red" and "green" terms in the CB vs. NS main datasets, but not in the NS1:NS2 random split, would imply that they cannot be attributed to random effects. We report detailed experimental results for this control set in Appendix A.3.

Preprocessing All posts were split at the sentence level and tokenized using the spacy toolkit. Sentences shorter than 4 or longer than 50 tokens were excluded from the analysis, as were sentences with a single token longer than 50 characters.

4.2 Experimental Results

4.2.1 RQ1 – Frequency and Relative Ratio

We extracted relative frequencies of all color terms and control adjectives (control set #1) in the two sub-corpora, along with their frequency ratios. Table 2 presents the results. Significant differences between the two populations exist (in both directions), but they are not restricted to the red-green terms. Control set #2 split yielded differences in a single color term and an adjective (see Appendix A.3). We conclude that no outright CB-linked differences can be found in the frequency-related usage of the two terms in our data.

color term	CB freq	NS freq	CB ratio	NS ratio
red	7.87e-5	7.72e-5	0.204	0.203
green	3.77e-5	3.49e-5*	0.098	0.092
black	8.50e-5	8.91e-5*	0.222	0.235
white	6.93e-5	7.24e-5	0.183	0.191
blue	4.77e-5	4.31e-5*	0.124	0.114
brown	1.92e-5	2.02e-5	0.051	0.053
gr[ae]y	4.69e-5	4.30e-5	0.037	0.032
yellow	1.41e-5	1.29e-5	0.034	0.034
pink	9.37e-6	8.67e-6	0.024	0.024
purple	8.74e-6	8.17e-6	0.023	0.022
total			1.0	1.0
hot	1.07e-4	1.11e-4*	0.206	0.206
social	1.12e-4	1.14e-4*	0.239	0.263
clear	1.12e-4	1.12e-4	0.235	0.223
tiny	5.26e-5	5.09e-5	0.101	0.096
flat	4.66e-5	4.47e-5	0.089	0.083
loose	2.20e-5	2.19e-5	0.042	0.040
petty	1.20e-5	1.19e-5	0.023	0.022
clever	1.29e-5	1.36e-5	0.024	0.025
royal	1.07e-5	1.18e-5	0.021	0.022
lame	1.03e-5	1.07e-5	0.020	0.020
total			1.0	1.0

Table 2: Relative frequencies (left) and relative ratios (right) of color terms in the language of CB and NS authors. Statistical significance of the differences was tested using a two-proportion z-test; "*" indicates significant difference at the level of p<.01.

4.2.2 RQ2 – Imageability of Modified Nouns

Given a sentence with a color term, we extract the noun modified by the term (where it exists) by applying dependency parsing[6] and detecting dependencies connecting the color term as ADJ to a NOUN via the AMOD dependency type, capturing both attributive and predicative adjective phrases. To eliminate spelling mistakes and parsing inaccuracies, we restrict the extracted noun set to the top-20,000 most frequent nouns in the corpus.

noun	orig	score	noun	orig	score
apple	✓	0.99	economy	✓	0.07
helicopter	✓	0.98	philosophy	✓	0.09
cabbage	✗	0.91	concern	✗	0.19
cobra	✗	0.93	purity	✗	0.18

Table 3: Example word imageability scores ("orig" denotes scores retrieved from Scott et al. (2019)).

[6] We make use of the spacy POS-tagger and dependency parser for this purpose: https://spacy.io/

type	sentence (verbatim)	noun	img score
A	His **red** **shirt** looks a little derpy	shirt	0.95
P	I could clearly see that the car didn’t stop although the **light** was **red**	light	0.75
A	typically, **green** **bars** and pixellation are a sign that a graphics card is crashing	bars	0.94
A	Wow... Can’t believe we’re going to have a **green** **Christmas** again	Christmas	0.70

Table 4: Example sentences with color terms in adjective phrases, along with the modified nouns’ imageability scores. "P" stands for predicative and "A" for attributive adjective phrase.

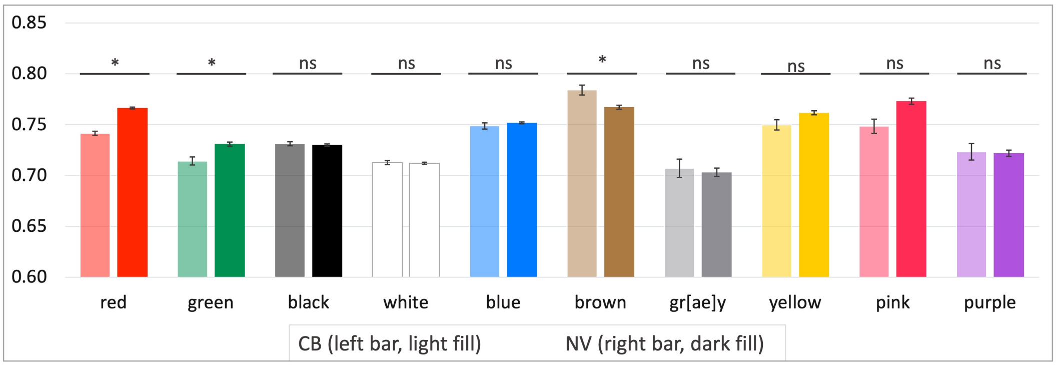

Figure 1: Mean and standard error of imageability scores of nouns modified by the color terms adjectives. "*" indicates significant difference at the level of p<.01; "ns" indicates non-significant difference. Note the large sample sizes for red and green (contributing to the significance of the findings), but much smaller samples for pink and yellow (Table 5). Considering the relatively high effect size for pink (Table 5), the high difference in mean scores would likely be triggered significant for sufficiently large data.

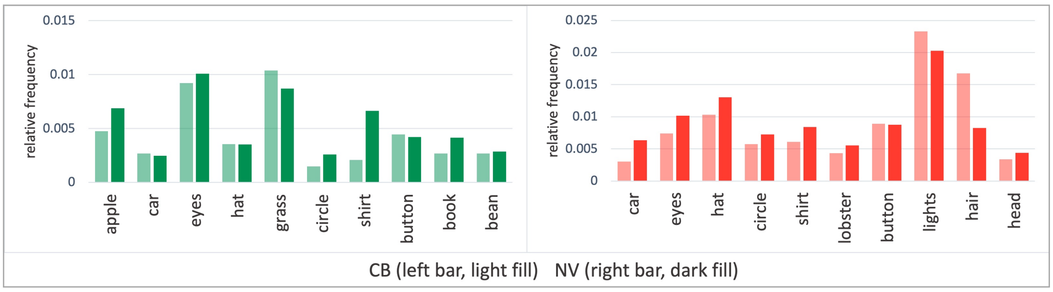

Figure 2: Top-10 most-imageable nouns used with "green" (left) and "red" (right) color terms in attributive and predicative expressions, and their relative frequencies in the CB (left, light fill) and NS (right, dark fill) datasets.

Inferring Missing Imageability Rankings The imageability rankings in Scott et al. (2019) cover about 3,000 of the 20,000 unique nouns identified in our CB and NS datasets. We exploit these ranking for supervision in extracting ratings for additional nouns in this work. Word embedding spaces have been shown to capture variability in affective dimensions (Hollis and Westbury, 2016) and word concreteness (Tsvetkov et al., 2013; Francis et al., 2021), where imageability is highly correlated with word concreteness (Scott et al., 2019). These findings imply that such semantic representations carry over information useful for the task of assessment of psycholinguistic properties.

We first normalized the imageability scores in Scott et al. (2019) into the 0-1 range for better interpretability. Using distributional word representations for the 5,500 annotated words, we trained a beta regression model[7] to predict imageability scores from word embeddings. We further used the trained model to infer imageability rankings for the unlabeled set of nouns. We used the *fasttext* word representations (Bojanowski et al., 2017), obtaining the highest Pearson’s correlations of 0.76 with the human annotated ratings on a held-out set of 500 nouns.[8] Table 3 presents a sample of nouns with contrasting imageability ratings – both original and inferred by the regression model.

[7] An alternative to linear regression in situations where the dependent variable is a proportion (0-1 range).

[8] Slightly lower correlations of 0.75 and 0.68 were obtained with word2vec (Mikolov et al., 2013) and Glove (Pennington et al., 2014) embeddings, respectively.

	CB		NS		
term	# sent	M(img)	# sent	M(img)	Cohen's d
red	8,249	0.744	37,213	0.768*	0.119
green	3,267	0.716	14,823	0.733+	0.076
black	9,462	0.733	45,763	0.731	-0.008
white	7,450	0.715	36,669	0.713	-0.007
blue	4,766	0.751	20,056	0.753	0.010
brown	1,292	0.788	6,227	0.769*	-0.094
gr[ae]y	1,125	0.707	4,237	0.703	-0.051
yellow	1,380	0.757	5,936	0.766	0.048
pink	846	0.75	3,915	0.775	0.120
purple	796	0.726	3,753	0.723	-0.014
hot	10,700	0.747	50,151	0.749	0.007
social	16,220	0.442	84,819	0.443	0.005
clear	6,295	0.530	27,110	0.531	0.004
tiny	6,796	0.608	30,014	0.608	0.001
flat	3,789	0.676	16,462	0.669	-0.029
loose	1,480	0.646	6,846	0.641	-0.020
petty	998	0.513	4,818	0.505	-0.045
clever	1,130	0.492	5,424	0.483	-0.042
royal	1,147	0.691	5,812	0.694	0.015
lame	930	0.524	4,355	0.536	0.053

Table 5: Mean imageability scores of nouns used with color terms and the control set #1 adjectives. "*" indicates significant difference at the level of p<.01, "+" indicates significant difference at the level of p<.05.

Assessing the Differences in Imageability Scores of Modified Nouns Next we estimated the differences across the imageability dimension in CB vs. NS authors, by recording the imageability score of modified nouns (where it exists) in the productions of the two populations. Table 4 presents example sentences with "red" and "green" terms and their modified nouns' imageability score in our dataset. We construct two lists of imageability scores: one for the nouns of CB speakers, and another for NS authors. Wilcoxon ranksum significance test was applied to the CB/NS pair of series of values, testing for significant difference, and Cohen's-d was calculated to indicate the magnitude of the effect.

Results and Discussion Figure 1 presents the differences in the mean imageability score of modified nouns, and Table 5 reports the full results. Significant differences exist for the "red" and "green" terms, where higher average imageability is observed in the NS authors, suggestive of less frequent use of these color terms to describe entities evoking a clear mental image in a speaker's mind by CB users. The opposite difference is evident for the brown color, possibly indicative of the compensatory usage of "brown" by CB users with high-imageability nouns. The relatively low effect size – 0.119, 0.076 and -0.094 for "red", "green", and "brown", respectively – imply subtle (yet reliably detected) differences in the two populations. No control set #1 adjectives exhibit significant differences, implying that the phenomenon is limited to color-term usage. The same experiment with the control set #2 yielded no significant differences, with an exception of "black" (with very low Cohen's-d=0.038) and "royal" (Cohen's-d=-0.093), which can be attributed to subtle topical differences in our data (Appendix A.3).

Figure 2 presents the top-10 most-imageable nouns used with "green" and "red" color terms in attributive and predicative expressions, and their relative frequencies in the CB and NS datasets. Out of ten nouns used in expressions with "green", CB authors use six less frequently than their NS counterparts do, and, similarly, seven out of ten nouns modified by "red". Note the possibly fixed meaning of "green car" (environmentally friendly) – an expression that is used slightly more frequently by the CB authors. Collectively, these results are suggestive of the less common use of adjective phrases including the "red" and "green" color terms with high-imageability nouns.

4.2.3 RQ3 – Contextual Predictability

Recent advances in deep neural networks (DNN) (LeCun et al., 2015; Bengio et al., 2021), and specifically, in training large DNN-based masked language models (MLM) (Vaswani et al., 2017) to predict the most plausible word given a sentence context – a technique known as context-based word prediction (Tenney et al., 2019) – offer novel ways to quantify differences in word usage while comparing large text corpora. Contextual word prediction (CWP) is a task involving two steps: First, a DNN-based language model is trained over large text corpora to predict masked words within sentence context. Second, the pretrained MLM is used to predict the probability of a word to appear in a specific masked position within a given sentence.

In this work, we use CWP to compare the "predictable" usage of color terms in language authored by CB and NS populations. For a set of sentences containing color terms (or control set #1 adjectives), we make use of BERT (Devlin et al., 2018) – an MLM pretrained on large text corpus to assess the predictability of a term in a given context.[9] We investigate RQ3 by comparing the average CWP scores for color and adjective terms under test in the

[9] We make use of the "bert-large-uncased" model; all words in this study were represented by a single token.

sentence (verbatim)	predicted rank
shows all enemies with a **red** square on them, it makes it easy to see enemies behind trees, ...	1
Well if it works then more **red**! get those chucks on and be ready :joy:	809
Bare feet on **green** grass, especially after a long day of having to wear shoes.	17
Nothing but the best for our boys in **green**.	362

Table 6: Example sentences with and BERT rank assigned to the (masked) red-green color term.

	CB		NS		
term	# sent	M(rank)	# sent	M(rank)	Cohen's d
red	11,332	109.1	50,801	94.8*	0.074
green	5,734	163.6	24,208	139.3*	0.109
black	12,850	74.2	62,379	72.3	0.013
white	10,514	99.0	51,741	95.6	0.019
blue	7,057	142.6	29,311	135.1	0.034
brown	2,900	161.5	14,028	148.2	0.056
gr[ae]y	1,692	225.1	6,969	213.2	0.043
yellow	1,900	154.8	7,885	148.3	0.029
pink	1,177	186.1	5,355	149.7*	0.156
purple	943	227.0	4,465	223.8	0.012
hot	16,362	64.5	79,978	60.6	0.027
social	16,897	32.4	88,476	27.4*	0.050
clear	20,149	51.8	89,361	48.9*	0.023
tiny	7,486	75.4	33,297	75.1	0.002
flat	6,909	96.3	30,898	91.0	0.029
loose	3,224	141.2	14,880	137.5	0.016
petty	1,516	156.6	7,428	159.5	-0.013
clever	2,300	122.9	10,830	108.2	0.079
royal	1,352	100.6	7,003	89.4	0.059
lame	1,653	185.3	8,047	189.0	-0.016

Table 7: Mean BERT rank predictions for a masked term. Results for both color terms and control set #1 adjectives are reported. "*" indicates significant difference at the level of p<.01.

CB and NS population of Reddit authors. Higher mean predictability would be indicative of a more typical way a term is used in its context.

Assessing Color Terms Predictability We predict the probability of a term to appear in a sentence context using BERT (Devlin et al., 2018). Due to the low ratio of CB people in the general population, we assume that the model broadly mirrors linguistic patterns of normal-sighted people. As a result, better predictability of a word by the model implies a more common usage.

We perform the following steps: (1) mask the designated term (either a color term or an adjective) using the <MASK> token provided by the BERT vocabulary; (2) use the probability distribution over the lexicon produced by the model as a prediction of the masked token. The prediction can be manifested in two ways: (a) the *probability value* produced by the softmax layer, and (b) the *rank* inferred by the probability distribution over the lexicon. For better interpretability, we make use of the latter (rank). Table 6 presents example sentences with red-green color terms and the BERT rank associated with the prediction of the (masked) term: "red" or "green".

Exceptionally high ranks were assigned to sentences with very atypical usage patterns of color terms, in particular, typos and ungrammatical usages. As a concrete example, the color term "red" in the sentence *"that was how i **red** it at first"* was assigned the rank of 5573 by the model since it is a typo, making it very unpredictable in this context. We therefore filtered out all sentences with a rank exceeding 1000 from this computation, as such rare cases significantly affect the average rank prediction.[10] This filtering approach reduces the total number of color-terms sentences by 9.3% and 8.2%, as well as control set #1 sentences by 5.6% and 4.9%, produced by the CV and NS authors, respectively. The suggested approach results in two lists of ranks for CB and NS productions. We further test the two lists for significant difference, and calculate Cohen's-d effect size.

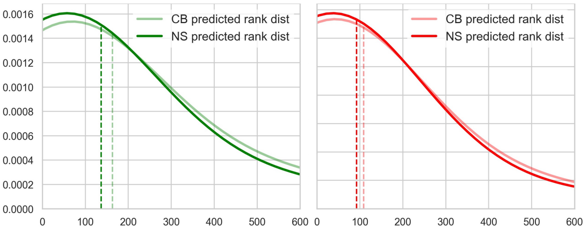

Figure 3: KDE plot of predicted rank for the red and green color terms in the CB vs. NS population; x-axis is pruned at 600; dashed line indicates the mean value.

Results and Discussion Table 7 reports the results. Evidently, "green", "red", and "pink" are the three terms exhibiting the highest Cohen's-d scores among all terms with significant differences. Interestingly, none of the adjective and other color terms with significant differences exceed the effect size of 0.05. The differences in "pink" could possibly be attributed to its proximity to the red color.

[10] The rank of 1000 was selected by qualitative evaluation over the set of 100 sentences with color terms.

Among the adjectives, only "social" and "clear" show significant difference, with very low effect size. Figure 3 illustrates the kernel density estimation (KDE) of predicted ranks for the green and red color terms in CB vs. NS speakers: the lower density for most predictable usages (around the rank of 0) and the slight right shift indicate less typical usage patterns of CB authors. No significant differences were found for colors in the control #2; detailed results are presented in Appendix A.3.

5 Discussion

We view the main contribution of this study in its large-scale data-driven empirical evidence for theoretically-motivated hypotheses on the effect of various sensory experiences on language learning and linguistic production. Human language production is a complex cognitive skill, where most psychological models agree on three stages: conceptualization, formulation and articulation. Conceptualization is considered to be the phase of selection and preparation of pre-linguistic information, relying also on extra-linguistic knowledge – among others, visual perception based on our sensory experience. LLMs, however large and complex, (presumably) lack this inherently-human cognitive skill, but rather operationalize linguistic production by stochastically reproducing language constructions they were exposed to, and generalizing to additional linguistically plausible patterns. Focusing on the effect of multi-modal input on human language production, we ask if bridging this gap is required for contemporary LLMs in order to generate fully naturalistic, human-like language. We believe that this work sheds new and interesting light on one of the core questions in language acquisition, and the ability of machines to achieve human-like linguistic competence.

6 Conclusions

We present a comparative analysis of the usage of "red" and "green" color terms in linguistic productions of red-green CB individuals and their NS counterparts. We show that color-blind speakers use these terms in less predictable contexts, and in linguistic environments evoking mental image to a lower extent. We believe that this study, along with the released dataset, helps better understanding of the effect of sensory experience on our language, and facilitates future research in this field.

7 Ethical Considerations

We use publicly available data to study how conceptual perception of colors by color-blind individuals is reflected in their spontaneous linguistic productions. The use of publicly available data from social media platforms, such as Reddit, may raise normative and ethical concerns. These concerns are extensively studied by the research community as reported in e.g., Proferes et al. (2021). Here we address two main concerns. (1) Anonymity: Data used for this research can only be associated with participants' user IDs, which, in turn, cannot be linked to any identifiable information. Additionally, this study uses the self-reported color blindness attribute, and does not infer any personal or demographic trait. (2) Consent: Jagfeld et al. (2021) debated the need to obtain informed consent for using social media data mainly because it is not straightforward to determine if posts pertain to a public or private context. Ethical guidelines for social media research (Benton et al., 2017) and practice in comparable research projects (Ahmed et al., 2017), as well as Reddit's terms of use, regard it as acceptable to waive explicit consent if users' anonymity is protected.

8 Limitations

The main limitation of our work stems from the difficulty to tease apart literal vs. figurative usages of color terms in the collected data. Certain expressions are inevitably ambiguous since they may be interpreted both literally and idiomatically; e.g., "green light" can refer metaphorically to a permission to go ahead, but also can literally mean a traffic light. However, while some of our filtered fixed expressions have a *possible* literal reading, typically many fewer have a *common* literal reading: these findings are consistent with those of earlier work on idiomatic expressions; for example, (Fazly et al., 2009) found that for 2/3 of the potentially-idiomatic expressions in their token dataset – i.e., phrases that could be used with either an idiomatic or literal meaning – over 75% of their usages were in an idiomatic reading.

While perfect distinction of fixed usages in impractical, we believe that our approach (Section 2.4) largely addresses this point by excluding usages that have a *common* fixed interpretation. Notably, when skipping this filtering step (i.e., considering all phrases with color terms), the results exhibit similar comparative patterns.

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A Appendix

A.1 List of Excluded Subreddits

This list of topical color-related threads (subreddits) could have potentially introduced a bias to our study, and therefore were excluded from data collection and analysis. We used an exhaustive list of subreddits including the term 'color' in their name:

r/color
r/ColorBlind
r/ColorBlindGamers
r/colorblindmemes
r/colorblindness
r/ColorBlindnessIsFun
r/ColorGrading
r/colorists
r/Colorization
r/colorizationrequests
r/colorizebot
r/colorize_bw_photos
r/ColorizedHistory
r/colorpie
r/colorsbot
r/ColorshopBattles
r/Colorslash
r/ColorThisSpace
r/Colourblind
r/ImaginaryColorscapes
r/thecolorless
r/UnitedColors
r/Shitty_Watercolour

r/WatercolorChallenge
r/Whatcoloristhis
r/Watercolor

A.2 Fixed Expressions with Color Terms Excluded from this Study

Table 8 reports the list of fixed constructions with color terms that were excluded from this work. We refer to some limitations related to filtering fixed expressions with color terms in Section 8.

term	nouns used in fixed constructions
red	alert, bull, cross, dot, flag, flags, herring, line, meat, pill, redemption, sox, tape, wedding, wings, zone
green	bay, card, cards, day, deal, earth, energy, lantern, light, line, mile, party, screen, text
black	box, flag, friday, guy, guys, hole, holes, magic, man, market, men, metal, mirror, ops, panther, people, person, widow, woman, women
white	dude, guy, guys, house, knight, male, males, man, men, nationalists, noise, people, person, privilege, sox, supremacist, supremacists, supremacy, walkers, women
blue	balls, blood, cheese, collar, jackets, jays, light, line, moon, shell, state, states, team, whale
brown	guy, people, recluse, switches
gr[ae]y	area, areas, chapter, cup, goo, goose, jedi, knights, man, market, matter, poupon, video, wardens, wind, worm, zone
yellow	fever, jacket, jackets, journalism, pages, submarine
pink	album, eye, floyd, guy, mast, panther, pistols, ranger, slime, slip, song, tax
purple	drank, gang, haze, heart, hearts, line, link, links, man, rain

Table 8: The list of fixed expressions with color terms excluded from this study.

A.3 Experimental Results for Control Set #2: NS Population Split

Tables 9, 10 and 11 report the results. Significant differences in frequencies are shown for "red" and "social" between the two sets (Table 9), "black" is the only color term exhibiting signinficant difference between the two groups with very low effect size (Cohen's-d=0.038) – this difference can be attributed to the very large sample size. BERT ranks predictions differ for the "loose" and "royal" adjectives; again, with very low effect sizes.

color term	NS1 freq	NS2 freq	NS1 ratio	NS2 ratio
red	2.07e-4	8.08e-5*	0.170	0.165
green	1.16e-5	1.49e-5	0.087	0.085
black	3.40e-5	4.12e-5	0.256	0.254
white	2.74e-5	3.68e-5	0.207	0.209
blue	1.57e-5	1.45e-5	0.118	0.119
brown	6.67e-5	6.02e-5	0.050	0.050
gr[ae]y	2.75e-5	2.30e-5	0.032	0.033
yellow	4.63e-5	4.89e-5	0.034	0.035
pink	2.91e-6	3.67e-6	0.022	0.023
purple	3.24e-6	3.01e-6	0.024	0.023
total			1.0	1.0
hot	2.71e-5	1.57e-5	0.210	0.208
social	3.75e-5	2.06e-5*	0.291	0.287
clear	2.81e-5	2.12e-5	0.218	0.219
tiny	1.08e-5	2.09e-5	0.083	0.086
flat	9.74e-6	7.47e-6	0.075	0.078
loose	5.28e-6	4.19e-6	0.041	0.039
petty	2.58e-6	1.39e-6	0.020	0.021
clever	2.63e-6	3.77e-6	0.020	0.022
royal	2.72e-6	1.78e-6	0.021	0.019
lame	2.28e-6	2.07e-6	0.017	0.017
total			1.0	1.0

Table 9: Relative frequencies (left) and relative ratios (right) of color terms in the language of CB and NS population. Statistical significance of the differences was tested using a two-proportion z-test; "*" indicates significant difference at the level of p<.01.

	NS1		NS2		
term	# sent	M(img)	# sent	M(img)	Cohen's d
red	10,358	0.774	47,512	0.772	-0.009
green	4,795	0.730	21,364	0.738	0.036
black	17,288	0.722	76,879	0.730*	0.038
white	13,618	0.719	61,705	0.718	-0.002
blue	7,045	0.764	31,588	0.765	0.004
brown	2,510	0.797	11,038	0.801	0.016
gr[ae]y	1,542	0.731	7,422	0.739	0.042
yellow	2,038	0.774	9,054	0.772	-0.007
pink	1,300	0.779	5,946	0.788	0.052
purple	1,385	0.727	5,946	0.746	0.088
hot	12,406	0.760	55,056	0.760	0.003
social	23,152	0.448	102,419	0.445	-0.016
clear	6,339	0.535	28,157	0.531	-0.018
tiny	6,559	0.609	30,082	0.611	0.007
flat	3,594	0.677	16,735	0.677	0.002
loose	1,693	0.635	7,441	0.652	0.069
petty	1,109	0.504	5,227	0.505	0.006
clever	1,079	0.478	5,130	0.486	0.034
royal	1,402	0.710	5,733	0.694*	-0.093
lame	938	0.538	4,399	0.538	0.001

Table 10: Mean imageability scores of nouns modified by color terms and the control set #1 adjectives in the control #2 NS split. "*" indicates significant difference at the level of p<.01.

	NS1		NS2		
term	# sent	M(rank)	# sent	M(rank)	Cohen's d
red	15,472	71.7	70,177	75.3	-0.022
green	8,500	103.5	37,775	107.8	-0.022
black	24,492	54.6	110,205	54.0	0.004
white	21,048	67.2	96,331	69.0	-0.012
blue	11,508	100.9	52,367	97.8	0.016
brown	4,870	111.6	22,440	109.9	0.008
grey	2,876	158.5	13,756	151.1	0.030
yellow	3,207	102.2	14,716	103.1	-0.005
pink	1,989	106.0	9,202	112.7	-0.035
purple	2,001	154.7	8,812	144.9	0.046
hot	20,637	55.2	91,331	56.4	-0.009
social	24,271	27.7	107,728	28.0	-0.003
clear	21,464	47.0	97,639	45.3	0.014
tiny	7,321	70.4	33,591	72.9	-0.017
flat	6,950	83.7	32,030	90.3	-0.038
loose	3,730	143.3	16,098	129.7*	0.061
petty	1,699	152.6	8,224	155.3	-0.012
clever	2,151	105.2	10,391	106.1	-0.005
royal	1,699	77.5	6,910	85.6*	-0.045
lame	1,761	179.9	8,231	184.4	-0.020

Table 11: Mean BERT rank predictions for a masked term. Results for both color terms and control set #1 adjectives in control set #2 NS split are reported. "*" indicates significant difference at the level of p<.01.